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Predictive Reliability

1.1. Concept of predictive reliability

Predictive reliability comes into play as soon as a product bill of material has been drawn up, the design files are sufficiently advanced and a certain number of tests have been carried out on prototypes. Its main objective is to check that the specifications in terms of reliability are being met and, of course, as we have seen in the foreword by Gilles Zwingelstein where he discusses operational safety (OS), to quantitatively provide input for maintenance (sizing of spare parts stocks), FMEA, testability and the various product fault trees.

To do this, a number of assumptions are made:

– Youth failures are not taken into account because they are filtered by the debugging process.

– Aging failures, except for certain subassemblies (fans, batteries, etc.), are not considered because they will not be visible during the operational life of the product. If this is the case, however, preventive maintenance actions or an estimate of the failure rate due to aging will then be taken into account for the final estimate.

– Premature aging of certain components due to a design weakness is not considered because it is determined by environmental robustness tests, derating analyses (compliance with a margin in relation to the design limit of a component) and worst case analyses, which allow the variability of the components to be taken into account, mechanical, thermal, electronic simulations, etc.

Thus, only the period of time when the product is mature (constant reliability) is considered in the predictive reliability analyses, as illustrated in the famous bathtub curve.

One possible method is the FIDES predictive reliability method. This is the method we use in this chapter.

Figure 1.1. *Illustration of the bathtub curve*

1.2. FIDES methodology

1.2.1. *Modeling reminder*

The objectives of the FIDES methodology (FIDES 2022) are, on the one hand, to enable a realistic assessment of the reliability of electronic products, including in systems that encounter harsh or very benign environments (storage), and, on the other hand, to provide a concrete tool for the construction and control of this reliability.

Its main characteristics are as follows:

– the existence of models for both electrical, electronic and electromechanical components as well as for electronic cards or certain subassemblies;

– the highlighting and consideration of all of the technological and physical factors that have an identified role in reliability;

– precise consideration of the life profile;

– taking into account accidental electrical, mechanical and thermal overloads (or overstress);

– taking into account failures linked to development, production, operation and maintenance processes;

– the ability to distinguish between multiple suppliers of the same component.

The FIDES reliability approach is based on the consideration of three components: technology, process and use. These components are considered for the entire lifecycle, from the product specification phase to the operation and maintenance phase.

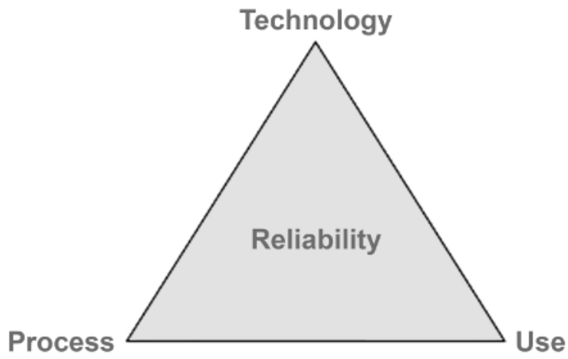

Figure 1.2. *Illustration of the pillars of the FIDES methodology. For a color version of this figure, see www.iste.co.uk/bayle/montecarlo.zip*

Technology covers both the article itself and its integration into the product. The *process* considers all practices and rules of the art from product specification to replacement. The use takes into account both the usage constraints defined by the product design and those in operation by the end user.

1.2.2. *Concept of life profile*

The creation of the life profile is a major step in estimating the product's predicted reliability and is often poorly specified and poorly analyzed. This is often because of the following factors:

– The proposed life profile is copied from one generation of equipment to another, which means that no one can justify the values of the parameters taken into account.

– The creation of the life profile is a joint effort between the client and the product designer. In fact, the client must specify the ambient external parameters that the product will be subjected to during its operational life, whereas the designer, on the basis of these data and the various characteristics of the product, will estimate its internal parameters.

Standard life profile									
		Temperature and humidity			Thermal cycling				Mechanics
Phase title	Calendar time (hours)	On/Off	Room temperatures (°C)	Humidity level (%)	ΔT (°C)	Number of cycles (/year)	Cycle duration (hours)	Maximal temperature during cycling (°C)	Random vibrations (Grms)
Off phase	5 110	Off	20	70	5	365	14	23	0.01
On phase	3 650	On	40	22	20	365	10	40	0.5

Table 1.1. *Example of a life profile*

– There is a great deal of variability in the levels of physical contribution. This is the case, for example, in the automotive sector, where the same type of car can have different life profiles depending on the type of driver, the type of road (motorway, city, countryside, mountain, etc.), the geographical location, the climatic conditions, etc.

Typically, predictive reliability estimates are made from constant values, leading to a single failure rate estimate, as illustrated in the example in Table 1.1 (FIDES 2022).

The values used are often average values, as in the example above, where the humidity level of 70% is a global average value. This approach has two drawbacks:

– the average value does not always represent an overall trend well, especially if the data are very dispersed;

– given that the laws of failure physics (Arrhenius, Coffin–Manson, etc.) are convex, an average value can then give imprecise results.

On the other hand, equating temperature variations (for example) can be an insurmountable task owing to different variabilities (day/night, seasonality, product use, etc.) that are difficult to model.

Therefore, Monte Carlo simulations can prove to be a more effective tool, particularly:

– a confidence interval is allowed for the estimated failure rate, which also makes it possible to respond, at least in principle, to certain comments made on this point (Pecht and Das 2020) in relation to the FIDES guide;

– by being able to estimate the relative importance of certain parameters of the life profile (temperature value or even of a particular phase of the profile considered), we can simplify it or pay particular attention to a given parameter.

1.3. Application example

Considering the following virtual example, the parameters Pi_Induit, Pi_Part and Pi_Process are normalized to 1.

Family	Technology family 1	Technology family 2	Technology family 3	Technology family 4	Pi Placement	Quantity
Capacitor	Aluminium capacitor	Liquid electrolyte			Analog function low level non interface	1
Capacitor	Ceramic capacitor	Type I	Category 2		Analog function low level non interface	1
Capacitor	Ceramic capacitor	Type II	non polymer terminaison		Analog function low level non interface	1
Capacitor	Ceramic capacitor	Type II	polymer terminaison	Category 2	Analog function low level non interface	1
Capacitor	Tantalum capacitors	Solid	CMS packaging		Analog function low level non interface	1
Discret semiconductor	Low power diode	Signal diode < 1A	SMD small signal L - lead plastic		Analog function low level non interface	1
Discret semiconductor	Low power diode	zener diode < 1.5W	SMD small signal L - lead plastic		Analog function low level interface	1
RF Discret semiconductor	Low power diode Si SiGe RF and HF		SMD small signal L - lead plastic		Analog function low level interface	1
Discret semiconductor	Power diode	zener diode > 1.5W	SMD small signal L - lead plastic		Analog power functions non interface	1
Discret semiconductor	Low power diode	Rectifying Diodes 1A to 3A	SMD small signal L - lead plastic		Analog function low level interface	1
Discret semiconductor	Power diode	Rectifying Diodes > 3A	SMD small signal L - lead plastic		Analog function low level non interface	1
Discret semiconductor	Low power transistor	Silicium bipolar < 5W	SMD small signal L - lead plastic		Analog function low level non interface	1
Discret semiconductor	Low power transistor	Silicium bipolar < 5W	SMD small signal L - lead plastic		Analog function low level non interface	1
Discret semiconductor	Low power transistor	Silicium MOS <5W	SMD small signal L-lead plastic		Analog function low level non interface	1
Fuse	CMS				Analog power function interface	1
Passive RF	Fixed				Analog function low level interface	1
Passive RF	Variables				Analog function low level interface	1
Piezoelectric component	Oscillator	SMD XO type			Analog function low level non interface	1
Connector	Coaxial	Soldered through hole			-	1
Connector	Circulars and rectangulars	Soldered through hole			-	1
Magnetic component	Multilayer inductor				Analog function low level non interface	1
Magnetic component	Transformator	Low power			Analog function low level non interface	1
Magnetic component	Transformator	Low power			Analog function low level non interface	1
Resistor	Resistive chip				Analog function low level non interface	1
Integrated circuit	Flash EEPROM EPROM memories	Numeric function none interface	TSOPI TSOPII		Numeric function non interface	1
Integrated circuit	Circuit Analog and Mixed circuits	Numeric function none interface	SSOP VSOP QSOP		Numeric function non interface	1
Integrated circuit	FGPGA CPLD FPGA Antifuse PAL	Numeric function none interface	PBGA BT		Numeric function non interface	1
Integrated circuit	Microprocessor Microcontrolor DSP	Numeric function none interface	PBGA CSP BT		Numeric function non interface	1
Optocouplor	Phototransistor	SO SOP SOL SOIC SOW			Analog function low level non interface	1
Printed circuit	210/210	Through holes			-	1

Table 1.2. *Example of a list of components based on FIDES*

1.3.1. *Classical estimation*

We obtain a failure rate of 8.3 Fits with the following distribution:

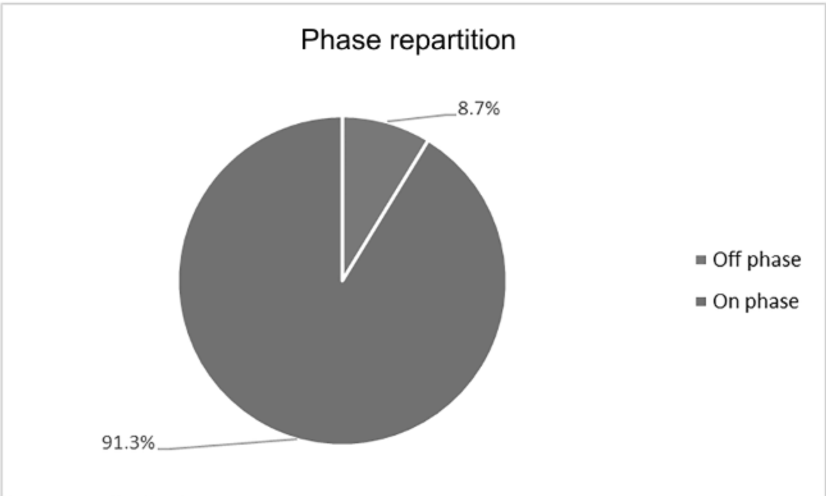

Figure 1.3. *Predicted failure rate repartition. For a color version of this figure, see www.iste.co.uk/bayle/montecarlo.zip*

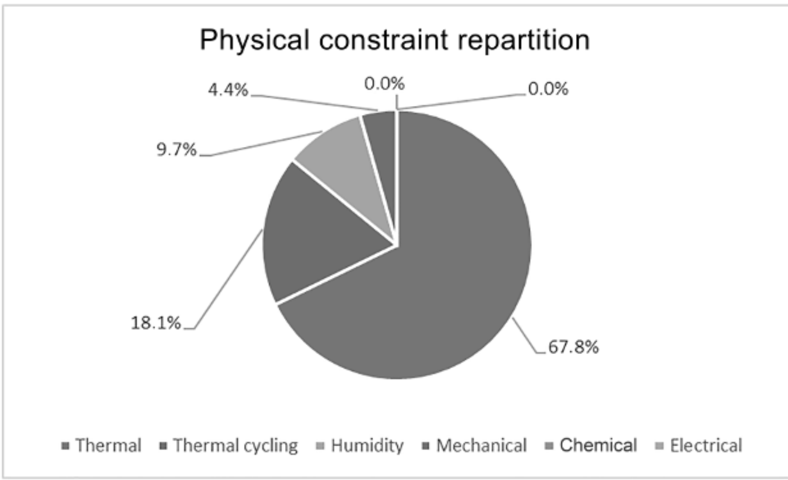

Figure 1.4. *Distribution of the predicted failure rate by physical contribution. For a color version of this figure, see www.iste.co.uk/bayle/montecarlo.zip*

The “Off” phase has a minor impact on the overall failure rate. It is therefore better to look at the sensitivity of the “On” phase parameters.

The physical, chemical and electrical contributions have no effect, whereas the thermal contribution represents more than two-thirds of the overall failure rate. A sensitivity analysis is then necessary for the temperature contribution.

1.3.2. *Estimation with a uniform law*

Instead of considering a single value for the levels of physical contributions, we propose here to have an interval of values following a uniform law and, in particular, to apply it to the thermal contribution. Thus, instead of considering a temperature of 40°C for the “On” phase, we propose taking into account a uniform law of parameters (35°C; 45°C).

From a confidence level of 90%, we obtain a failure rate of 8.4 Fits with a confidence interval of (6.96; 10.12) Fits. We carried out 1,000 simulations, and the failure rate was obtained by taking the arithmetic mean of the 1,000 simulated failure rates. From these results and sorting them in ascending order, we obtain, for a confidence level of 90%, the lower bound at the 50th rank and the upper bound at the 950th rank. If we had chosen a uniform law with the parameter (20°C; 60°C), we would have obtained an average failure rate of 9.98 Fits with a confidence interval of (4.67; 20.19) Fits.

REMARK.–

These simulation results indicate the following:

– The average value of the failure rate is higher than the “classical” value, especially since the extent of the normal distribution is large. Importantly, the uniform distribution $U[\theta a, \theta b]$ with $\theta b > \theta a$ is involved in the Arrhenius distribution in the following form: $\lambda(\theta) = C.\exp\left(\frac{-\mathrm{Ea}}{\mathrm{Kb}.U[\theta a,\theta b]}\right)$. The activation energy represents the sensitivity of the failure rate to temperature θ, and the failure rate will be much more strongly impacted for temperature θb than for θa because of the convexity of the exponential function.

– We can also notice the same trend with the confidence interval, which “widens” all the more as the extent of the uniform law is important.

These two phenomena are more important as the activation energy is high.

1.3.3. *Estimation with a normal distribution*

However, since the simulated temperature values are all equiprobable, this is not very realistic because the probability of having extreme values in the considered interval is rather low. Additionally, we can replace the uniform law with a normal law. However, this approach requires more information on the temperature values than the previous approach does.

Let us therefore consider a normal distribution with parameters N (40°C; 5°C). From a confidence level of 90%, we obtain an average failure rate of 8.6 Fits with a confidence interval of (6.15; 12.3) Fits.

However, the normal law has two drawbacks in the area of reliability:

– Its symmetry about the mean is because there is no physical reason for this to be the case.

– Its definition ranges from $-\infty$ to $+\infty$, which generally poses a problem, particularly for humidity levels.

To avoid the first drawback, we can use the Weibull law, which can be very asymmetrical depending on the value of the shape parameter. For the second drawback, for example, for the humidity rate, we can use a beta law whose domain of definition is [0; 1], which is therefore in line with the humidity rate, which can vary from 0 to 100%.

1.4. Maintaining a reliability specification

One of the goals of predictive reliability is to verify compliance with a specification. Typically, this is achieved by making a "brutal" comparison between the reliability estimate and the allocated target.

For example, taking the previous example where we had an objective failure rate of 10 Fits, the classic analysis leads to this objective being met since the estimated failure rate is lower (8.4 Fits). However, is this really the case? In other words, is the fact that it is lower than the objective sufficient to conclude?

The advantage of taking into account uncertainties in the life profile allows us to obtain an estimate but also a confidence interval. Thus, to have good confidence in the holding of the specification, we will rather compare the objective to the upper bound of the estimated failure rate. In the previous section, we had a bilateral confidence interval (lower and upper bounds). Here, we will choose a unilateral upper bound, that is, the 900th rank (90% confidence level for 1,000 simulations).

If we take the example with a uniform law on the temperature of the "On" phase, we obtain a unilateral upper bound of 9.9 Fits, which is very close to the objective.

NOTE.–

Generally, the reliability objective is expressed in terms of the following:

– Probability of failure for a given time Tobj and confidence level for maintenance-free applications such as space, nuclear or military. The probability of failure and the failure rate are, for an exponential distribution in accordance with the assumption of section 1.1, linked by the following relationship:

$$F(Tobj) = 1 - \exp(-\lambda . Tobj)$$

– MTBF for most applications that have maintenance actions. The failure rate and MTBF are related by the following relationship:

$$MTBF = \frac{1}{\lambda}$$

1.5. Summary

– Estimating the predicted reliability of a system is usually essential during its design phase.

– The life profile that the system will undergo during its operation has a major influence on the estimation of the predicted reliability.

– The levels of physical contribution of the life profile considered are often very dispersed over time, whereas generally, the predictive reliability is estimated from average levels.

– For greater realism, we propose replacing, when necessary, the average levels with probability laws, based on the information collected, in the form of Monte Carlo simulations.

– The advantage of these simulations is that they can estimate the importance of certain phases of the life profile and therefore the relevance of the assumptions made on the levels of corresponding physical contributions (temperature, vibration, humidity).